Generation of Complex Patterns using Coupled Generative Adversarial Networks

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Abstract

This study reveals what kind of temporal and spatial patterns form when learning in an adversarial relationship between two individuals. The model was implemented by coupling generative adversarial networks, which are well-known in the field of machine learning. The obtained temporal patterns resulted in chaos with a positive Lyapunov exponent for time-series learning, whereas spatial pattern learning produced structured patterns with a higher fractal dimension, not just more complexity with a higher entropy.

Introduction

The simulation studies for communication emergence in Alife aim to reveal how communication signals are organized to make sense with other individuals (Marocco et al., 2003; Hashimoto and Ikegami, 1996; Shibuya et al., 2018). In those simulations, other individuals are always cooperative and the signals tend to converge on simple symbolic usages, such as alarm sounds used by animals. How, then, can human language and some bird songs, which form complex signal patterns, emerge?

The studies in which complex patterns are produced involve dilemmatic or competitive environments instead of simple cooperative relationships (Suzuki and Kaneko, 1994; Hashimoto and Ikegami, 1996; Iizuka and Ikegami, 2004; Moran and Pollack, 2017). In particular, Suzuki and Kaneko (1994) showed that the parameters of the logistic function evolved to the edge of chaos in generating time series in a situation where individuals want to imitate but not be imitated. We call this situation an adversarial imitation. The ability to imitate profitable and useful behaviors is beneficial. However, for those performing the behavior, being imitated loses the benefit. Brood parasitism, used by some birds, is a good example. The strategy of imitating and not-being-imitated can be evolutionarily dominant. In this study, we use deep learning methods to investigate what kind of time series or spatial patterns adversarial imitation generates and how the patterns can be structured using a simulation-based synthetic approach.

Coupled Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a technique that imitates real data (e.g., images) to create artificial data that does not actually exist but is realistic (Goodfellow et al., 2014). We use GANs to model adversarial imitation.

Time series generation

We first describe the model of applying coupled GANs to time series generation, simulating a situation in which two agents engage in adversarial imitation. Figure 1 presents an overview of the simulation model. Each agent consists of a time series generator and discriminator. The generator generates its own time series, feeding back its output to the input at each step. The imitation time series are generated while inputting the opponent's time series at each step. The discriminator receives each generated time series as input and outputs whether it is its own or the opponent's. The discriminator is trained such that it can recognize the time series generated by its own generator as its own and the imitation time series as the opponent's. The teaching signals are given as to who outputs the time series. The generator is trained such that its discriminator recognizes the own time series as its own, and the opponent's discriminator is fooled into recognizing the generated imitation time series as the opponent's own time series.

The top graphs in Fig.2 are bifurcation diagrams showing the convergence points of the time series generated by the trained generators at each learning epoch. The random initialization of the generators resulted in monotonically converging dynamics; however, as the learning progressed, we observe bifurcations of the generated time series and dynamics changing from periodic to more complex trajectories. The graphs on the lower right of Fig.2 present examples of the complex trajectories. The Lyapunov exponents calculated by differentiating the generator networks show that generators produced a chaotic trajectory (see lower left of Fig.2).

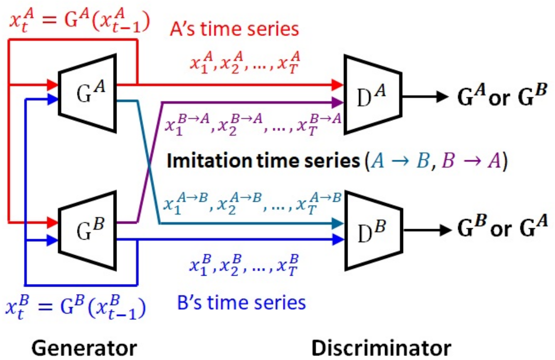

Figure 1: Coupled GANs for time series generation

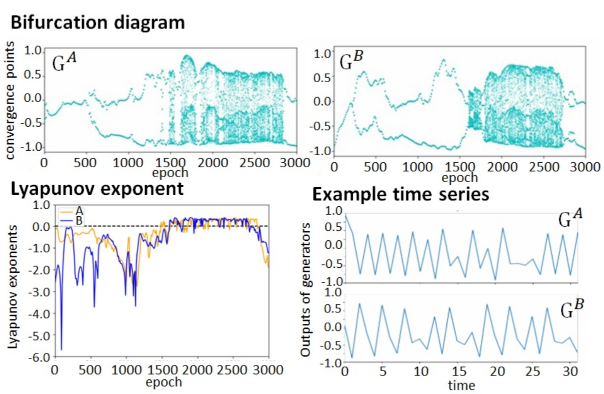

Figure 2: Learning results of time series generation

Spatial pattern generation

We then applied the Coupled GANs to generate spatial patterns. Figure 3 presents an overview of our simulation model. The spatial pattern generators were implemented using feed-forward networks with convolution layers, whereas the time series in the previous experiment was generated in a recurrent manner. The generators generated grayscale images of size 128×128 from random values, similar to the original GANs. These generators and discriminators were trained using adversarial imitation in the same manner as the previous experiment. To show that mutual adversarial imitation learning produced structural patterns, we compared it to the unidirectional condition, in which only one individual performed adversarial imitation learning.

The graphs on the left in Fig.4 show the patterns generated by generators G^{A} and G^{B} with eight different random z values under the mutual conditions. The generations of images by G^{A} and G^{B} are independent, but they generated similar patterns owing to the imitation effect. However, they did not maintain the same pattern. The generated patterns became equally cluttered at the beginning because all network parameters were initialized with random values. In addition,

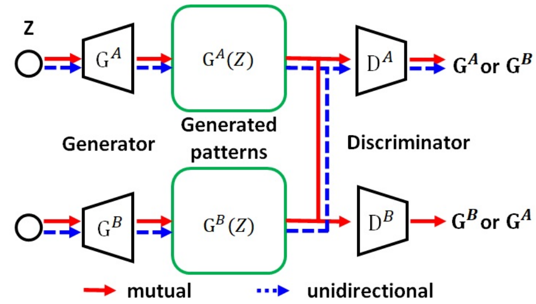

Figure 3: Coupled GANs for spatial pattern generation

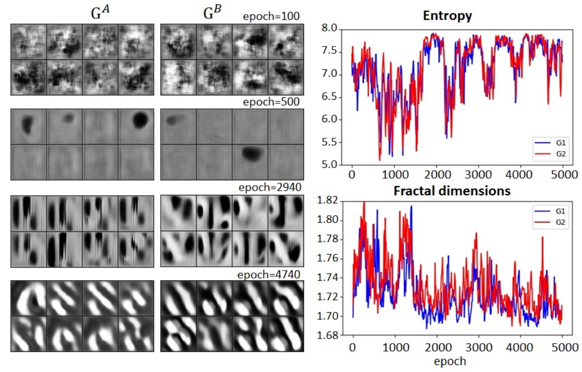

Figure 4: Generated patterns and changes of entropy and fractal dimensions

as the learning process progressed, in the mutual adversarial imitation learning, the generated patterns had a type of global pattern instead of a locally cluttered pattern. Conversely, in the unidirectional adversarial imitation learning, the generated patterns became locally detailed and cluttered (not shown).

To show the progress of complication and structuring under mutual adversarial imitation learning, entropy and fractal dimensions were computed (see the images on the right in Fig.4). In the mutual adversarial imitation learning, the entropy and fractal dimension oscillated. The entropy sometimes decreased, and the pattern became less cluttered. The fractal dimension temporarily increased. In the unidirectional adversarial imitation learning, we observed that entropy simply increased and that the fractal dimension stagnated at a relatively low value. These results indicate that mutual adversarial imitation learning generates not only complex patterns, but also formed structural patterns measurable in the fractal dimension.

Conclusion

We showed that adversarial imitation learning can increase the complexity of patterns and structure them both temporally and spatially. If only one side of the discriminators was trained, it simply produced a messy spatial pattern. This suggests that mutual learning is necessary for the formation of patterns with structure rather than mere clutter.

Acknowledgements

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